

Cross-Layer Control for Worse Case Delay Guarantees in Heterogeneous Powered Wireless Sensor Network via Lyapunov Optimization

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Abstract—The delay guarantee is a challenge in wireless sensor networks (WSNs), where energy constraints must be considered. The coexistence of renewable energy and electricity grid is expected as a promising energy supply manner for WSNs to remain function for a potentially infinite lifetime. In this paper, we address cross-layer control to guarantee worse case delay for Heterogeneous Powered (HP) WSNs. We design a novel virtual delay queue structure, and apply the Lyapunov optimization technique to develop cross-layer control algorithm only requiring knowledge of the instantaneous system state, which provides efficient throughput-utility, and guarantees bounded worst-case delay. We analyze the performance of the proposed algorithm and verify the theoretic claims through the simulation results. Compared to the existing work, the algorithm presented in this paper achieves much higher optimal objective value with ultra-low data drop due to the proposed novel virtual queue structure.

Index Terms—Cross-Layer Control, Delay Guarantee, Heterogeneous Energy, Wireless Sensor Network, Lyapunov Optimization

I. INTRODUCTION

Wireless sensor networks (WSNs) have been an active research area during the last two decades. By embedding low-cost, low-power, small-size, and multifunctional sensor nodes into the environment, a variety of parameters such as pressure, humidity, temperature, and vibration intensity are measured and wirelessly transmitted to a processing center. Based on these collected parameters, the center then analyzes any potential problems, and even rapidly responds to real-time events with appropriate actions. Due to self-organization, rapid deployment, easy maintenance, and reduced cost, WSNs provides several potential advantages over traditional wired system. The existing and potential applications of WSNs span a very wide range, including industrial monitoring and control [1], building automation [2], video surveillance [3], and so on.

Traditionally, sensor nodes are powered by a non-rechargeable battery with limited energy storage capacities. Thus, the main research efforts in developing WSNs have focused on how to improve the energy efficiency with respect to limited battery energy [4], [5]. Recently, energy harvesting (EH) technique utilized in wireless system has attracted attention [6]. However, due to the low recharging rate and the time-varying profile of the energy replenishment process, renewable

energy cannot guarantee to provide the perpetual operation for WSNs in most application scenarios. The coexistence of renewable energy and electricity grid, called as Heterogeneous Power (HP) in this paper, is expected as a promising energy supply manner to remain function for a potentially infinite lifetime in wireless system [7].

There are a number of different real-time requirements in WSNs applications, for instance, manufacturing and process automation and motion control. Thus, delay constrained data collection in WSNs has been studied to some extent [8], [9]. However, there are only few works for diminishing delay in EH-WSNs, which are mainly based on duty cycle adjustment [10]. However, these works do not investigate to reduce queueing delay with deterministic or probabilistic guarantee. In a multihop network, the network delay performance depends heavily on the queue length at every node along the multihop route. When the data arrive at a node, they have to be processed and forwarded. If the data arrive faster than the node can process them, the node puts them into the queue until it can get around to transmit them. As a queue begins to fill up due to the traffic arriving faster than it can be processed, the amount of delay a packet experiences going through the queue increases. The longer is the line of data waiting to be transmitted, the longer is the average queueing delay. In practice, each node only has a finite buffer to hold the data. Thus, a node may experience a full queue that may potentially cause the loss of data traffic, leading to QoS degradation. Although the queueing delay have been extensively addressed in multi-hop wireless networks (See the related works in Section II). However, these works are not readily extendable to WSNs, where energy constraints must be considered. Furthermore, most of existing works provide only an average delay bound, can not give bounds on the delays of individual sessions, and even yield unbounded worst-case delays. It is vital to propose a scheme to guarantee worst-case delay for WSNs in a variety of applications.

In this paper, we will address cross-layer control to guarantee worse case delay for HP-WSNs. through designing a novel virtual delay queue structure, and applying the Lyapunov optimization technique. The key contributions of this paper are as follows.

- We consider heterogeneous energy supplies from renewable energy, electricity grid and mixed energy, multiple energy consumptions due to sensing, transmission and reception, and multi-dimension stochastic natures due to EH profile, electricity price and channel condition. We

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develop a novel virtual delay queue scheme to share the burden of actual packet queue backlogs to guarantee specific delay performances and finite data buffer sizes. Finally, we formulate a discrete-time stochastic delay-aware cross-layer control problem for achieving the optimal trade-off between the time-average throughput utility and electricity cost subject to the data and energy queuing stability constraints, and to guarantee worst case delay for HP-WSNs.

- To obtain a distributed and low-complexity solution, we apply the Lyapunov drift-plus-penalty technique [31] to transform the stochastic control problem into a deterministic optimization problem, which can be solved by a greedy algorithm at every time-slot only requiring knowledge of the instantaneous system state. Furthermore, by exploiting the special structure of the deterministic optimization problem, we design a distributed algorithm which decomposes the overall problem into the energy management subproblem, the physical layer subproblem, the network layer subproblem, and the transport layer subproblem.
- We analyze the performance of the proposed distributed algorithm. We show that a control parameter V enables an explicit trade-off between the average utility and queue backlog. Specifically, the proposed distributed algorithm is shown only achieve a time average utility that is within $\mathcal{O}(1/V)$ of the optimal network utility for any $V \geq 0$, while ensuring that the average network backlog is $\mathcal{O}(V)$, when the system state is independent and identically distributed (i.i.d.). Finally, extensive simulations verify the theoretic claims, and demonstrate that the proposed distributed algorithm achieves much higher optimal objective value with ultra-low data drop, compared to the existing work.

Throughout this paper, we use the following notations. The probability of an event A is denoted by $\Pr(A)$. For a random variable X , its expected value is denoted by $\mathbb{E}[X]$ and its expected value conditioned on event A is denoted by $\mathbb{E}[X|A]$. The indicator function for an event A is denoted by $\mathbf{1}_A$; it equals 1 if A occurs and is 0 otherwise. $[x]^+ = \max(x, 0)$.

The remainder of the paper is organized as follows. In Section II, we introduce the related works. In Section III, we give the system model and problem formulation. In Section IV, we present the distributed cross-layer optimization algorithm using Lyapunov optimization. In Section V, we present the performance analysis of our proposed algorithm. Simulation results are given in Section VI. Concluding remarks are provided in Section VII.

II. RELATED WORK

A. Optimization for EH node and EH-WSNs

Recently, a great deal of research efforts have been devoted to investigate the energy management and data transmission schemes in EH node. Sharma et al. in [11] obtain two energy management policies to achieve the optimal throughput and the minimal mean delay. Srivastava et al. in [12] give an energy

management scheme to achieve the optimal utility asymptotically while keeping both the battery discharge and data loss probabilities low. Zhang et al. in [13] address the adaptive decision of the sampling rate for EH sensor node with a limited battery capacity to maximize the overall network performance. Mao et al. in [14] study the energy allocation for sensing and transmission in an EH sensor node with a rechargeable battery and a finite data buffer. However, different nodes in networks may have quite different workload requirements and available energy sources. Some works address the optimal design for EH-WSNs. Mao et al. in [15] address the joint control of the data queue and battery buffer to maximize the long-term average sensing rate of EH-WSNs under certain QoS constraints for the data and battery queues. Chen et al. in [16] address the joint problem of energy allocation and routing to maximize the total system utility, without prior knowledge of the replenishment profile. Sarkar et al. in [17] design routing and scheduling policies that optimize network throughput in EH-WSNs. Gatzianas et al. in [18] design an on-line adaptive transmission scheme to achieve close-to-optimal utility performance and to ensure the data queue stability for wireless networks with rechargeable battery. Huang et al. in [19] develop the Energy-limited Scheduling Algorithm (ESA) and Modified-ESA (MESA) algorithm to achieve an explicit and controllable tradeoff between optimality gap and queue sizes for EH-WSNs. Tapparello et al. in [20] proposed the joint optimization scheme of source coding and transmission to minimize the reconstruction distortion cost for EH-WSNs with the correlated sources measurement. However, delay metrics is not considered in the works mentioned above. Furthermore, almost no works, except [14] [20], study the joint energy allocation for communication module and sensing module together. In addition, due to the low recharging rate and the time-varying profile of the energy replenishment process, sensor nodes solely powered by harvested energy can not guarantee to provide reliable services for the perpetual operation.

B. Delay-aware optimization for multi-hop wireless networks

The optimization-based design methodology has been extensively developed to handle the queueing delay in multi-hop wireless networks [21]. In [22], Gupta et al. analyze the delay performance of a multihop wireless network with a fixed route and arbitrary interference constraints. In [23], Venkataramanan et al. derive bounds on the best performance of end-to-end buffer usage over a network with general topology and with fixed, loop-free routes. In [24], Bui et al. propose a novel architecture and algorithm to improve the delay performance of the back-pressure algorithm. In [25], Ying et al. propose a hop-count based queueing structure to adaptively select a set of optimal routes based on shortest-path information, resulting in much smaller end-to-end packet delays as compared to the traditional back-pressure algorithm. In [26], Xiong et al. propose a novel link rate allocation strategy and a regulated scheduling strategy to develop delay-aware joint flow control, routing, and scheduling algorithm to achieve loop-free route and optimal network utilization for general multi-hop networks. However, none of the above-mentioned

works provides explicit end-to-end delay guarantees. There are several works aiming to address end-to-end delay or buffer occupancy guarantees in multihop wireless networks. In [27], Huang et al. proposes a fully-distributed joint congestion control and scheduling algorithm that can guarantee order optimal per-flow end-to-end delay and utilize close-to-half of the system capacity for multihop wireless networks with fixed-routing under the one-hop interference constraint. In [28], Le et al. investigate the performance of joint flow control, routing, and scheduling algorithms that achieve high network utility and deterministically bounded backlogs in wireless networks with finite buffers. In [29], Xue et al. propose a joint congestion control, routing, and scheduling problem in a multihop wireless network to satisfying per-flow average end-to-end delay constraints and minimum data rate requirements. Note that the delay threshold is a time-averaged upper bound, not a deterministic one. These prior works may yield unbounded worst-case delays. In [30], Neely et al. design an opportunistic scheduling algorithm that guarantees all sessions have a bounded worst case delay. However, these works are not readily extendable to multihop WSNs, where energy constraints must be considered. It is more challenge to deal with queue delay in EH-WSNs.

III. SYSTEM MODEL AND PROBLEM FORMULATION

Consider a multi-hop WSNs with N nodes that operates in discrete time with normalized time slots $t \in \mathcal{T} = \{0, 1, \dots, T\}$. Let $\mathcal{N} = \mathcal{N}_H \cup \mathcal{N}_G \cup \mathcal{N}_M = \{1, \dots, N\}$ denote the set of sensor nodes in the network. \mathcal{N}_H is the set of nodes powered by EH, called EH nodes, \mathcal{N}_G is the set of nodes powered by electricity grid (EG), called EG nodes, \mathcal{N}_M is the set of Mixed energy (ME) nodes powered by both EH and EG. $\mathcal{L} = \{(m, n), m, n \in \mathcal{N}\}$ represents the set of communication links. Each node has multiple sensor interfaces and can measure multiple information. We assume that there are F traffic sessions, which can be measured by source nodes $n \in \mathcal{N}_s$, $\mathcal{N}_s \subset \mathcal{N}$. Let $\mathcal{F} = \{1, \dots, F\}$ denote the set of traffic sessions in the network.

A. Data Queue Dynamic

The data backlog for each session $f \in \mathcal{F}$ and each node $n \in \mathcal{N}$ in slot t is denoted by $Q_n^f(t)$. The queue dynamics is given by:

$$Q_n^f(t+1) \leq [Q_n^f(t) - \sum_{b \in \mathcal{O}(n)} \mu_{nb}^f(t) - D_n^f(t)]^+ + \sum_{a \in \mathcal{I}(n)} \mu_{an}^f + \mathbf{1}_n^f r_n^f(t) \quad (1)$$

Where $[a]^+$ denotes $\max\{a, 0\}$, $\mathcal{O}(n)$ denotes the set of nodes b with $(n, b) \in \mathcal{L}$. $\mathcal{I}(n)$ denotes the set of nodes m with $(m, n) \in \mathcal{L}$. The service decision variable $\mu_{nb}^f(t)$ represents the amount of packets of session f successfully served from node n to node b on slot t . The drop decision variable $D_n^f(t)$ represents the number of packets of session f that dropped by node n on slot t . The admission decision variable $r_n^f(t)$ represents the amount of packets of session f that sensed by

node $n \in \mathcal{N}_s$ on slot t . We assume that the drop decision $D_n^f(t)$ and service decision $\mu_{nb}^f(t)$ are made at the beginning of each slot, and the admission decision $r_n^f(t)$ will be made at the end of each slot. There exist a maximum transmission rate μ_{\max} over any link and a maximum amount D_{\max} of data we are allowed to drop on slot t for any session, which are both finite constants. Then the drop decisions and service decisions will be subjected to the constraint $D_n^f(t) \leq D_{\max}$ and $\sum_{f \in \mathcal{F}} \mu_{nb}^f(t) \leq \mu_{\max}$, respectively. The admission decisions $r_n^f(t)$ is also subjected to the constraint $r_n^f(t) \leq R_{\max}$, where R_{\max} is a finite constant.

B. A Novel Virtual Queue Structure

Now we consider the delay of data in the data queue. [32] developed a virtual queue called ϵ -persistent service queue for each node. Here we propose a novel virtual queue structure, called as the delay queue, to guarantee the worst case delay of all sessions.

For each node $n \in \mathcal{N}$ and for each session $f \in \mathcal{F}$, we define a virtual queue $\tilde{Q}_n^f(t)$ with the queue dynamics as follows:

$$\tilde{Q}_n^f(t+1) = \begin{cases} \tilde{Q}_n^f(t) - \sum_{b \in \mathcal{O}(n)} \mu_{nb}^f(t) - D_n^f(t) + \varepsilon_n^f, & Q_n^f(t) > \rho \tilde{Q}_n^f(t) \quad (2a) \\ \tilde{Q}_n^f(t) - \mu_{\max}^{\text{out}} - D_{\max} + \varepsilon_n^f, & Q_n^f(t) \leq \rho \tilde{Q}_n^f(t) \quad (2b) \end{cases}$$

Where $\tilde{Q}_n^f(0) = 0$, and ε_n^f is a constant satisfied with $0 < \varepsilon_n^f \leq D_{\max}$. Shown in Eq. (2a)(2b), there always exists a persistent arrival with the size ε_n^f to the virtual queue at each slot.

If there exists a scheduling algorithm that maintains bounded $Q_n^f(t)$ and $\tilde{Q}_n^f(t)$, the worst case delay will also be bounded, which will be proved in Theorem 1.

Theorem 1. For all slots $t \in \mathcal{T}$ and traffic sessions $f \in \mathcal{F}$, suppose a scheduling algorithm is used to ensure that the queue $Q_n^f(t)$ and $\tilde{Q}_n^f(t)$ have the finite upper bound Q_{\max} and \tilde{Q}_{\max} , respectively. Assuming First Input First Output (FIFO) service, then the worst case delay of all non-dropped data in node n can be defined as $W_{n,\max}^f$, which is given by:

$$W_{n,\max}^f = \max \left\{ \left[(1 + \rho) Q_{\max} + \rho \tilde{Q}_{\max} \right] / (\rho \varepsilon_n^f), \right. \\ \left. 2\tilde{Q}_{\max} / (\mu_{\max}^{\text{out}} + D_{\max} - \varepsilon_n^f) \right\} \quad (3)$$

Proof: Please see Appendix A.

To achieve the minimal worst case delay W_{\max}^f in node n , according to (3), we can see the optimal value of ρ^* should be set

$$\rho^* = \frac{Q_{\max} (\mu_{\max}^{\text{out}} + D_{\max} - \varepsilon_n^f)}{2\tilde{Q}_{\max} \varepsilon_n^f - (Q_{\max} + \tilde{Q}_{\max}) (\mu_{\max} + D_{\max} - \varepsilon_n^f)} \quad (4)$$

C. Data sensing/processing

At time slot t , node n will measure information source F_n independently, where $F_n \in \mathcal{F}_n$. \mathcal{F}_n is the set of information source, $\mathcal{F}_n = \{1, 2, 3, \dots, F_n\}$ and $\mathcal{F} = \bigcup_{n \in \mathcal{N}_s} \mathcal{F}_n$. The measured samples of the session F_n is compressed with rate $r_n^f(t)$. We define $p_f^S(r_n^f(t))$ as the function of energy consumption for sensing/processing at a particular rate $r_n^f(t)$. The relationship between $p_f^S(r_n^f(t))$ and $r_n^f(t)$ can be regarded as linearity, i.e. $p_f^S(r_n^f(t)) = \tilde{p}_f^S r_n^f(t)$ [20]. \tilde{p}_f^S denotes the energy consumption for sensing/processing per unit data of the f -th session. Similarly, we use \tilde{p}_f^R to denote the energy consumption for node n to receive one data from the neighbor nodes in the network.

D. Data transmission

We define the transmission power allocation matrix for data transmission at slot t as below:

$$\mathbf{p}^T(t) = (p_{mn}^T(t), (m, n) \in \mathcal{L})$$

$p_{mn}^T(t)$ denotes the transmission power allocated to link (m, n) at slot t . Then for each node n , the power consumption should follow below condition:

$$\sum_{b \in \mathcal{O}(n)} p_{nm}^T(t) \leq P_n^{\max}, n \in \mathcal{N} \quad (5)$$

P_n^{\max} is the maximal transmission power limitation at node n , which is assumed to be a finite constant.

For WSNs, there always exist interference between different links while transmission. We denote the signal to interference plus noise ratio (SINR) of link (n, b) as the function of transmission power $\mathbf{p}^T(t)$ and network channel state $\mathbf{S}^C(t)$:

$$\begin{aligned} \gamma_{nb}(t) &\triangleq \gamma_{nb}(\mathbf{p}^T(t), \mathbf{S}^C(t)) \\ &= \frac{S_{nb}^C(t) p_{nb}^T(t)}{N_0^b + \sum_{a \in \mathcal{J}_{n,b}} \sum_{(a,m) \in \mathcal{L}} S_{ab}^C(t) p_{am}^T(t)} \end{aligned} \quad (6)$$

Where $\mathbf{S}^C(t)$ present the network channel state matrix, $\mathbf{S}^C(t) = \{S_{nm}^C(t), (n, m) \in \mathcal{L}\}$. $S_{nb}^C(t)$ denotes the link fading coefficient on link (n, b) at slot t , which is randomly varying over time slots in an i.i.d. fashion according to a potentially unknown distribution and taking non-negative values from a finite but arbitrarily large set \mathcal{S}^C . N_0^b presents the background noise power at node b , $\mathcal{J}_{n,b}$ is the set of nodes whose transmission may interfere to the link (n, b) , excluding node n .

Furthermore, we define $C_{nb}(t) = \log(1 + \gamma_{nb}(t))$ as the link capacity. So we can get that the data transmission constraint condition:

$$\sum_{f \in \mathcal{F}} \mu_{nb}^f(t) \leq C_{nb}(t) \quad \forall n \in \mathcal{N}, \forall b \in \mathcal{O}(n) \quad (7)$$

In the high-SINR case, $\log(\gamma_{nb}(t))$ would have been a good approximation of $\log(1 + \gamma_{nb}(t))$. Thus, we will regard $\tilde{C}_{nb}(t) = \log(\gamma_{nb}(t))$ as the link capacity in the following context. So the constraint (7) can be transformed into:

$$\sum_{f \in \mathcal{F}} \mu_{nb}^f(t) \leq \tilde{C}_{nb}(t), \forall n \in \mathcal{N}, \forall b \in \mathcal{O}(n) \quad (8)$$

E. Energy Consumption Model

According to the above description, we can get the total energy consumption of node n at slot t to accomplish the tasks, including data sensing/processing, data transmission and data reception:

$$\begin{aligned} p_n^{Total}(t) &= \sum_{f \in \mathcal{F}} \tilde{p}_f^S r_n^f(t) + \sum_{b \in \mathcal{O}(n)} p_{nb}^T(t) \\ &\quad + \tilde{p}_f^R \sum_{a \in \mathcal{I}(n)} \sum_{f \in \mathcal{F}} \mu_{an}^f(t) \end{aligned} \quad (9)$$

F. Energy Queue Dynamic

We define $E_n(t)$ as the energy queue in node n at slot t . The EH nodes can harvest energy $e_n(t)$ from the environment (such as sunshine), then store the energy into the battery. The energy in EG nodes is generally acquired from the electricity grid. Similarly for the EH nodes, the energy in the EG nodes will also be stored into the battery. The energy supplied by the electricity grid is denoted as $g_n(t)$. Different from the EH nodes and EG nodes, the ME nodes can both harvest energy from environment and acquire energy from the electricity grid.

Then we can give the energy queue dynamic for any node n in the network as follows:

$$\begin{aligned} E_n(t+1) &= E_n(t) + \mathbf{1}_{n \in \mathcal{N}_H \cup \mathcal{N}_M} e_n(t) \\ &\quad + \mathbf{1}_{n \in \mathcal{N}_G \cup \mathcal{N}_M} g_n(t) - p_n^{Total}(t) \end{aligned} \quad (10)$$

Where $\mathbf{1}_{n \in \mathcal{N}_H \cup \mathcal{N}_M}$ and $\mathbf{1}_{n \in \mathcal{N}_G \cup \mathcal{N}_M}$ are indicator functions. At any slot t , the total energy consumption must satisfy the following energy-availability constraint:

$$E_n(t) \geq p_n^{Total}(t), \quad \forall n \in \mathcal{N} \quad (11)$$

Suppose the batteries have the limited capacity θ_n^E . So we have

$$E_n(t) + \mathbf{1}_{n \in \mathcal{N}_H \cup \mathcal{N}_M} e_n(t) + \mathbf{1}_{n \in \mathcal{N}_G \cup \mathcal{N}_M} g_n(t) \leq \theta_n^E \quad (12)$$

The energy acquiring $e_n(t)$ and $g_n(t)$ should satisfy the constraint $0 \leq e_n(t) \leq h_n(t)$ and $0 \leq g_n(t) \leq g_n^{\max}$, respectively. $h_n(t)$ represents the available amount of harvesting energy at slot t , which should satisfy the condition $0 \leq h_n(t) \leq h_{\max}$. Let $\mathbf{S}^H(t) = (h_n(t), n \in \mathcal{N}_H \cup \mathcal{N}_M)$ denote the harvestable energy state vector, which is randomly varying over time slots in an i.i.d. fashion according to a potentially unknown distribution and taking non-negative values from a finite but arbitrarily large set \mathcal{S}^H .

G. Electricity Price

We denote the cost of per unit electricity as $p_n^G(t)$. In general, $p_n^G(t)$ depends on the electricity drawn from the electricity grid $g_n(t)$ and electricity price state $S_n^G(t)$. It means that $p_n^G(t)$ will change over time and space. We assume that is a stationary process with i.i.d.. Assume that $S_n^G(t)$ takes non-negative values from a finite but arbitrarily large set \mathcal{S}^G . Denote the price state vector as $\mathbf{S}^G = \{S_n^G(t), n \in \mathcal{N}_G \cup \mathcal{N}_M\}$. Then we can give the price function as:

$$p_n^G(t) = p_n^G(S_n^G(t), g_n(t))$$

For each given $S_n^G(t)$, $p_n^G(t)$ is assumed to be a increasing and continuous convex function of $g_n(t)$.

H. Optimization Problem

Let $U_n^f(x)$ be a continuous, concave, and non-decreasing utility function with $U_n^f(0) = 0$, $n \in \mathcal{N}$, $f \in \mathcal{F}$. Assume that β_n^f is the maximum right-derivative of $U_n^f(x)$, and $0 < \beta_n^f < \infty$. We use schedule algorithms that stabilize all the queues in the system. Then for each session $f \in \mathcal{F}_n$ with source node $n \in \mathcal{N}_s$, we have the following condition according to the Rate Stability Theorem, i.e., Theorem 2.4 in [32]:

$$\bar{r}_n^f \leq \bar{\mu}_n^f + \bar{d}_n^f \quad n \in \mathcal{N}_s, f \in \mathcal{F}_n$$

Where \bar{r}_n^f is the time average rate of accepting packets, $\bar{\mu}_n^f$ is the time average rate of total served packets and \bar{d}_n^f denotes the time average amount of dropping packets for session f at node n . As a result, we can use the value of $\bar{r}_n^f - \bar{d}_n^f$ to denote the throughput of the source node n for session f . And we desire a solution to the following problem:

$$\text{Maximize: } \sum_{n \in \mathcal{N}_s} \sum_{f \in \mathcal{F}_n} U_n^f(\bar{r}_n^f - \bar{d}_n^f) \quad (13)$$

Subject to: all queues $Q_n^f(t)$ are mean rate stable

Notice that it will be puzzled if Lyapunov optimization is directly used to solve problem (13).

Considering the characteristic of the function $U_n^f(x)$, the following inequality should be satisfied,

$$U_n^f(\bar{r}_n^f - \bar{d}_n^f) \geq U_n^f(\bar{r}_n^f) - \beta_n^f \bar{d}_n^f$$

Then, let us consider the problem (14)

$$\text{Maximize: } \sum_{n \in \mathcal{N}_s} \sum_{f \in \mathcal{F}_n} U_n^f(\bar{r}_n^f) - \sum_{n,f} \beta_n^f \bar{d}_n^f \quad (14)$$

Subject to: all queues $Q_n^f(t)$ are mean rate stable

We can see that the problem (14) is to maximize the utility of average throughput while minimizing the amount of average drop packets as much as possible. If we can transform the problem (13) to (14), the problem can be solved simply by applying Lyapunov optimization. [32] provides a method that completes the transform successfully.

According to the Jensen's inequality for concave functions which states that:

$$\mathbb{E} \{U_n^f(\bar{r}_n^f(t))\} \leq U_n^f(\mathbb{E} \{\bar{r}_n^f(t)\}), \quad \mathbb{E} \{\bar{r}_n^f(t)\} \in \mathbb{R}$$

We can get that the condition below would be satisfied for all $t > 0$:

$$\begin{aligned} \frac{1}{t} \sum_{\tau=0}^{t-1} U_n^f(\bar{r}_n^f(\tau)) &\leq U_n^f\left(\frac{1}{t} \sum_{\tau=0}^{t-1} \bar{r}_n^f(\tau)\right), \quad \frac{1}{t} \sum_{\tau=0}^{t-1} \bar{r}_n^f(\tau) \in \mathbb{R} \\ \text{and } \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E} \{U_n^f(\bar{r}_n^f(\tau))\} &\leq U_n^f\left(\frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E} \{\bar{r}_n^f(\tau)\}\right) \\ &\quad , \quad \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E} \{\bar{r}_n^f(\tau)\} \in \mathbb{R} \end{aligned}$$

Take limits as $t \rightarrow \infty$, then

$$\overline{U_n^f(\bar{r}_n^f)} \leq U_n^f(\bar{r}_n^f), \quad \bar{r}_n^f \in \mathbb{R} \quad (15)$$

where $U_n^f(\bar{r}_n^f)$ and \bar{r}_n^f are defined as:

$$\begin{aligned} \overline{U_n^f(\bar{r}_n^f)} &\triangleq \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E} \{U_n^f(\bar{r}_n^f(\tau))\}, \\ \bar{r}_n^f &\triangleq \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E} \{\bar{r}_n^f(\tau)\} \end{aligned}$$

As presented in [32], we need to construct a virtual queue to complete the transform. For each session $f \in \mathcal{F}_n$ at node $n \in \mathcal{N}_s$, we define a virtual flow state queue $Z_n^f(t)$, which has the queue dynamic as follows:

$$Z_n^f(t+1) = \max \{ (Z_n^f(t) - r_n^f(t) + \tilde{r}_n^f(t)), 0 \} \quad (16)$$

Where $\tilde{r}_n^f(t)$ is a auxiliary variable that satisfies the constraint $\tilde{r}_n^f(t) \leq R_{\max}$. We call it as the virtual input rate.

At last, we will take the electricity price into consideration. The finally goal is to achieve the optimal trade-off between the time-average throughput utility of the source nodes and the time average cost of energy consumption in electricity grid. The optimization problem **P1** can be given as:

$$\begin{aligned} \text{Maximize: } \varpi_1 &\left(\sum_{n \in \mathcal{N}_s} \sum_{f \in \mathcal{F}_n} \overline{U_n^f(\tilde{r}_n^f(t))} - \sum_{n,f} \overline{\beta_n^f D_n^f(t)} \right) \\ &- (1 - \varpi_1) \varpi_2 \sum_{n \in \mathcal{N}_G \cup \mathcal{N}_M} \overline{p_n^G(t) g_n(t)} \quad (17) \end{aligned}$$

Subject to: (5), (8), (11), (12)

$$\bar{r}_n^f \leq \bar{r}_n^f \quad n \in \mathcal{N}_s, f \in \mathcal{F}_n \quad (18)$$

$$0 \leq \tilde{r}_n^f(t) \leq R_{\max} \quad n \in \mathcal{N}_s, f \in \mathcal{F}_n \quad (19)$$

$$0 \leq r_n^f(t) \leq R_{\max} \quad n \in \mathcal{N}_s, f \in \mathcal{F}_n \quad (20)$$

$$0 \leq D_n^f(t) \leq D_{\max} \quad f \in \mathcal{F}, n \in \mathcal{N} \quad (21)$$

$$0 \leq e_n(t) \leq h_n(t) \quad n \in \mathcal{N} \quad (22)$$

$$0 \leq g_n(t) \leq g_n^{\max} \quad n \in \mathcal{N} \quad (23)$$

$$0 \leq h_n(t) \leq h_{\max} \quad n \in \mathcal{N} \quad (24)$$

all queues $Q_n^f(t)$, $\tilde{Q}_n^f(t)$, $E_n(t)$, $Z_n^f(t)$ are mean rate stable with queuing dynamics

(1), (2a), (2b), (10) and (16) for $\forall n \in \mathcal{N}$,

$\forall f \in \mathcal{F}$, respectively. (25)

ϖ_1 is a weight parameter to combine these two objective functions together into a single one. ϖ_2 is a mapping parameter to ensure the objective functions at the same level.

IV. CROSS-LAYER CONTROL VIA LYAPUNOV OPTIMIZATION

Now we will apply the Lyapunov optimization algorithm to solve the problem **P1**. First, define the network state vector at time slot t as $\Psi(t) \triangleq [\mathbf{Q}(t), \tilde{\mathbf{Q}}(t), \mathbf{Z}(t), \mathbf{E}(t)]$ and define the Lyapunov function $L(\Psi(t))$ by:

$$\begin{aligned} L(\Psi(t)) &= \frac{1}{2} \sum_{n \in \mathcal{N}} \sum_{f \in \mathcal{F}} \left[(Q_n^f(t))^2 + (\tilde{Q}_n^f(t))^2 \right] \\ &+ \frac{1}{2} \sum_{f \in \mathcal{F}} (Z_n^f(t))^2 + \frac{1}{2} \sum_{n \in \mathcal{N}} (E_n(t) - \theta_n^E)^2 \quad (26) \end{aligned}$$

So the conditional Lyapunov drift at time slot t can be given by:

$$\Delta(\Psi(t)) = \mathbb{E}\{L(\Psi(t+1)) - L(\Psi(t)) | \Psi(t)\} \quad (27)$$

At last, we can define the drift-plus-penalty function as:

$$\Delta_V(\Psi(t)) = \Delta(\Psi(t)) - V\mathbb{E}\{\phi(t) | \Psi(t)\} \quad (28)$$

Where

$$\begin{aligned} \phi(t) = & \varpi_1 \left(\sum_{n \in \mathcal{N}_s} \sum_{f \in \mathcal{F}_n} U_n^f(\tilde{r}_n^f(t)) - \sum_{n,f} \beta_n^f D_n^f(t) \right) \\ & - (1 - \varpi_1) \varpi_2 \sum_{n \in \mathcal{N}_G \cup \mathcal{N}_M} p_n^G(t) g_n(t) \end{aligned} \quad (29)$$

So we can find the drift-plus-penalty satisfied the inequality as (30). Taking expectation on both sides of the inequality and combining (9) with (30), we can transform (30) into (31).

Where B is a constant and satisfies:

$$\begin{aligned} B \geq & \frac{1}{2} \sum_{n \in \mathcal{N}} \sum_{f \in \mathcal{F}} \left[\sum_{b \in \mathcal{O}(n)} \mu_{nb}^f(t) + D_n^f(t) - \sum_{a \in \mathcal{I}(n)} \mu_{an}^f(t) \right. \\ & \left. - \mathbf{1}_n^f r_n^f(t) \right]^2 + \frac{1}{2} \sum_{f \in \mathcal{F}} [\tilde{r}_n^f(t) - r_n^f(t)]^2 \\ & + \frac{1}{2} \sum_{n \in \mathcal{N}} \sum_{f \in \mathcal{F}} \left[\sum_{b \in \mathcal{O}(n)} \mu_{nb}^f(t) + D_n^f(t) - \varepsilon_n^f \right]^2 \\ & + \frac{1}{2} \sum_{n \in \mathcal{N}} [\mathbf{1}_{n \in \mathcal{N}_H \cup \mathcal{N}_M} e_n(t) + \mathbf{1}_{n \in \mathcal{N}_G \cup \mathcal{N}_M} g_n(t) \\ & - p_n^{Total}(t)]^2 \end{aligned} \quad (32)$$

According to (8) and (19)-(24), we can see such a constant must be exist.

A. Framework of CLCA

We now present our algorithm CLCA. The main design principle of CLCA is to minimize the R.H.S. of (31) subject to the constraints (5),(8),(11),(12), (19)-(24). The framework of CLCA is described in Algorithm 1 summarized in TABLE I.

TABLE I
ALGORITHM: CLCA

- 1: Initialization: The perturbed variables θ_n^E , persistent arrival ε_n^f and the penalty parameter V are given, each queue backlog is set to zero.
- 2: Observe $S^C(t)$, $S^H(t)$, $S^G(t)$ while given $\Psi(t)$ (the current queue backlogs are known each slot)
- 3: Choose the optimal variables to minimize the right-hand-side (RHS) of (31) subject to the constraints (5),(8),(11),(12), (19)-(24).
- 4: Update data queues, delay queues, Z queues and the energy queues according to (1), (2a), (2b), (10) and (16), respectively.
- 5: Repeat step 2 to step 4 at each time slot $t \in \mathcal{T}$.

Remark Note that the algorithm CLCA only requires the knowledge of the instant values of $S^C(t)$, $S^H(t)$, $S^G(t)$. It does not require any knowledge of the statistics of these stochastic processes. The remaining challenge is to solve the problem **P2**, which is discussed below.

B. Components of CLCA

At each time slot t , after observing $S^C(t)$, $S^H(t)$, $S^G(t)$, all components of CLCA is iteratively implemented in the distributed manner to cooperatively solve the problem **P2**. Next, we describe each component of CLCA in detail.

1) *Source Rate Control*: For each session $f \in \mathcal{F}_n$ at source node $n \in \mathcal{N}_s$, choose $r_n^f(t)$ to solve

$$\begin{aligned} \min_{r_n^f} & [Q_n^f(t) - Z_n^f(t) - (E_n(t) - \theta_n^E) \tilde{p}_f^S] \cdot r_n^f(t) \\ \text{s.t.} & 0 \leq r_n^f(t) \leq R_{\max} \end{aligned} \quad (33)$$

It is easy to find that we can choose $r_n^f(t)$ by

$$r_n^f(t) = \begin{cases} R_{\max} & Q_n^f(t) < Z_n^f(t) + (E_n(t) - \theta_n^E) \tilde{p}_f^S \\ 0 & Q_n^f(t) \geq Z_n^f(t) + (E_n(t) - \theta_n^E) \tilde{p}_f^S \end{cases}$$

2) *Virtual Input Rate Control*: For each $f \in \mathcal{F}_n$, choose $\tilde{r}_n^f(t)$ to solve

$$\begin{aligned} \min_{\tilde{r}_n^f} & Z_n^f(t) \cdot \tilde{r}_n^f(t) - V\varpi_1 U_n^f(\tilde{r}_n^f(t)) \\ \text{s.t.} & 0 \leq \tilde{r}_n^f(t) \leq R_{\max} \end{aligned} \quad (34)$$

which is a convex optimization problem, and thus has a global optimum.

3) *Packet Drop Decision*: For each session $f \in \mathcal{F}$ and each node $n \in \mathcal{N}$, choose $D_n^f(t)$ to solve,

$$\begin{aligned} \max_{D_n^f} & (\tilde{Q}_n^f(t) + Q_n^f(t) - V\varpi_1 \beta_n^f) \cdot D_n^f(t) \\ \text{s.t.} & 0 \leq D_n^f(t) \leq D_{\max} \end{aligned} \quad (35)$$

We can get the solution as follows:

$$D_n^f(t) = \begin{cases} D_{\max} & Q_n^f(t) + \tilde{Q}_n^f(t) > V\varpi_1 \beta_n^f \\ 0 & Q_n^f(t) + \tilde{Q}_n^f(t) \leq V\varpi_1 \beta_n^f \end{cases}$$

Remark According to the solution above, we can see that there will be a frequent packet drop as the backlog increases. Due to the persistence arrival of the delay queue, the delay queue backlog will increase much faster than the data queue. If the sum of $Q_n^f(t)$ and $\tilde{Q}_n^f(t)$ is larger than $V\varpi_1 \beta_n^f$, the queue begin to drop packets.

4) *Join Optimal Transmission Power Allocation, Routing and Scheduling*: As described in previous subsection, the transmission rate over the link is associated with the transmission power. We shall consider the two variables together. So we have the optimization problem of transmission rate and

$$\begin{aligned}
\Delta_V(\Psi(t)) \leq & B - \mathbb{E} \left\{ V \varpi_1 \left(\sum_{n \in \mathcal{N}_s} \sum_{f \in \mathcal{F}_n} U_n^f(\tilde{r}_n^f(t)) - \sum_{n,f} \beta_n^f D_n^f(t) \right) - V(1 - \varpi_1) \varpi_2 \sum_{n \in \mathcal{N}_G \cup \mathcal{N}_M} p_n^G(t) g_n(t) | \Psi(t) \right\} \\
& + \sum_{n \in \mathcal{N}} \sum_{f \in \mathcal{F}} Q_n^f(t) \mathbb{E} \left\{ \sum_{a \in \mathcal{I}(n)} \mu_{an}^f(t) + \mathbf{1}_n^f r_n^f(t) - \sum_{b \in \mathcal{O}(n)} \mu_{nb}^f(t) - D_n^f(t) | \Psi(t) \right\} \\
& + \sum_{n \in \mathcal{N}} \sum_{f \in \mathcal{F}} \tilde{Q}_n^f(t) \mathbb{E} \left\{ \varepsilon_n^f - \sum_{b \in \mathcal{O}(n)} \mu_{nb}^f(t) - D_n^f(t) | \Psi(t) \right\} + \sum_{n \in \mathcal{N}_s} \sum_{f \in \mathcal{F}_n} Z_n^f(t) \mathbb{E} \{ \tilde{r}_n^f(t) - r_n^f(t) | \Psi(t) \} \\
& + \sum_{n \in \mathcal{N}} (E_n(t) - \theta_n^E) \mathbb{E} \{ \mathbf{1}_{n \in \mathcal{N}_H \cup \mathcal{N}_M} \cdot e_n(t) + \mathbf{1}_{n \in \mathcal{N}_G \cup \mathcal{N}_M} \cdot g_n(t) - p_n^{Total}(t) | \Psi(t) \} \quad (30)
\end{aligned}$$

$$\begin{aligned}
\mathbb{E} \{ \Delta_V(\Psi(t)) \} \leq & B + \sum_{n \in \mathcal{N}_s} \sum_{f \in \mathcal{F}_n} [Q_n^f(t) - Z_n^f(t) - (E_n(t) - \theta_n^E) \tilde{p}_f^S] \cdot r_n^f(t) \\
& + \sum_{n \in \mathcal{N}_s} \sum_{f \in \mathcal{F}_n} [Z_n^f(t) \cdot \tilde{r}_n^f(t) - V \varpi_1 U_n^f(\tilde{r}_n^f(t))] - \sum_{n \in \mathcal{N}} \sum_{f \in \mathcal{F}} [\tilde{Q}_n^f(t) + Q_n^f(t) - V \varpi_1 \beta_n^f] \cdot D_n^f(t) \\
& + \sum_{n \in \mathcal{N}_H \cup \mathcal{N}_M} (E_n(t) - \theta_n^E) \cdot e_n(t) \\
& + \sum_{n \in \mathcal{N}_G \cup \mathcal{N}_M} [(E_n(t) - \theta_n^E) + V(1 - \varpi_1) \varpi_2 S_n^G(t)] \cdot g_n(t) \\
& - \sum_{n \in \mathcal{N}} \sum_{f \in \mathcal{F}} \sum_{b \in \mathcal{O}(n)} [Q_n^f(t) - Q_b^f(t) + (E_b(t) - \theta_b^E) \tilde{p}_b^R + \tilde{Q}_n^f(t)] \mu_{nb}^f(t) \\
& - \sum_{n \in \mathcal{N}} \sum_{b \in \mathcal{O}(n)} (E_n(t) - \theta_n^E) p_{nb}^T(t) + \sum_{n \in \mathcal{N}} \sum_{f \in \mathcal{F}} \tilde{Q}_n^f(t) \varepsilon_n^f \quad (31)
\end{aligned}$$

transmission power as follow,

$$\begin{aligned}
\max \quad & \sum_{n \in \mathcal{N}} \sum_{b \in \mathcal{O}(n)} \sum_{f \in \mathcal{F}} \omega_{nb}^f(t) \mu_{nb}^f(t) \\
& + \sum_{n \in \mathcal{N}} \sum_{b \in \mathcal{O}(n)} (E_n(t) - \theta_n^E) p_{nb}^T(t) \quad (36) \\
s.t. \quad & 0 \leq \sum_{f \in \mathcal{F}} \mu_{nb}^f(t) \leq \tilde{C}_{nb}(t), \forall n \in \mathcal{N}, \forall b \in \mathcal{O}(n) \\
& 0 \leq \sum_{b \in \mathcal{O}(n)} p_{nm}^T(t) \leq P_n^{\max}, \forall n \in \mathcal{N}, \forall b \in \mathcal{O}(n)
\end{aligned}$$

where

$$\omega_{nb}^f(t) \triangleq Q_n^f(t) - Q_b^f(t) + (E_b(t) - \theta_b^E) \tilde{p}_b^R + \tilde{Q}_n^f(t) \quad (37)$$

as the weight of session f over link (n, b) .

Remark In traditional back-pressure algorithm, the network stability is achieved at the expense of large packet queue backlogs. In contrast, in our proposed algorithm CLCA, the realistic packet queue backlogs are also shared by our proposed virtual delay queues. We assign the weight as a sum of actual packet queue backlog differential and the backlog of a designed virtual queue, shown in (37). Thus, the network stabilization is achieved with the help of virtual queue structures that do not contribute to delay in the network.

a) *Routing and scheduling*: Define $\omega_{nb}^{f*}(t) \triangleq \max_{f \in \mathcal{F}} \omega_{nb}^f(t)$ as the corresponding optimal weight of link

(n, b) , then the traffic session f^* is selected for routing over link (n, b) when $\omega_{nb}^{f*}(t) > 0$.

That is, we will allocate all the link capacity of (n, b) to session f^* , set $\mu_{n,b}^{f*}(t) = \tilde{C}_{nb}(\mathbf{p}^{T*}, \mathbf{S}^C(t))$, where \mathbf{p}^{T*} is the transmission powers and $\mathbf{S}^C(t)$ is the current channel state.

b) *Transmission power allocation*: after routing and scheduling, we will try to make decision about the transmission power. Now we will observe the current channel state $\mathbf{S}_C(t)$ and select the transmission powers p^{T*} by solving the following optimization problem,

$$\begin{aligned}
\max_{p_{nm}^T} \quad & \sum_{n \in \mathcal{N}} \sum_{b \in \mathcal{O}(n)} [\omega_{nb}^{f*}(t) \tilde{C}_{nb}(t) + (E_n(t) - \theta_n^E) p_{nb}^T(t)] \quad (38) \\
s.t. \quad & 0 \leq \sum_{b \in \mathcal{O}(n)} p_{nm}^T(t) \leq P_n^{\max}, \forall n \in \mathcal{N}
\end{aligned}$$

To solve the problem (38), we develop a variable $\hat{p}_{nm}^T(t) = \log(p_{nm}^T(t))$, and take logarithm of both sides of the constraint in problem (38), then the problem can be equivalently transformed into

$$\begin{aligned}
\max_{\hat{p}_{nm}^T} \quad & \sum_{n \in \mathcal{N}} \sum_{b \in \mathcal{O}(n)} [\omega_{nb}^{f*}(t) \Psi_{nb}(\hat{p}_{nm}^T(t)) \\
& + (E_n(t) - \theta_n^E) e^{\hat{p}_{nm}^T(t)}] \quad (39) \\
s.t. \quad & \log \left(\sum_{b \in \mathcal{O}(n)} e^{\hat{p}_{nm}^T(t)} \right) - \log(P_n^{\max}) \leq 0, \forall n \in \mathcal{N}
\end{aligned}$$

Where $\Psi_{nb}(\hat{p}_{nm}^T(t))$ is defined as

$$\Psi_{nb}(\hat{p}^T(t)) \triangleq \log(\gamma_{nb}(t)) = \log S_{nb}^C + \hat{p}_{nb}^T(t) - \log \left(N_0^b + \sum_{a \in \mathcal{J}_{n,b}} \sum_{(a,m) \in \mathcal{L}} \exp(\log S_{ab}^C + \hat{p}_{am}^T(t)) \right) \quad (40)$$

We can see $\Psi_{nb}(\hat{p}^T)$ is a strictly concave function of a logarithmically transformed power vector $\hat{p}^T(t)$. Due to (12), we have $E_n(t) \leq \theta_n^E$, so $(E_n(t) - \theta_n^E) e^{\hat{p}_{nm}^T(t)}$ is a strictly concave function of $\hat{p}^T(t)$. Thus, the objective of (39) is a strictly convex in $\hat{p}^T(t)$. As is also a strictly convex in $\hat{p}^T(t)$, the problem (39) is a strictly convex optimal problem, which has the global optimum.

Now we propose a distributed iterative algorithm base on block coordinate descent (BCD) method to solve the problem (39) distributively. We assume that a single block of variables is optimized while the remaining blocks are fixed at each iteration. Let t_i denote the i -th iteration at time slot t . Then for each node $n \in \mathcal{N}$ at iteration t_i , the blocks $\hat{\mathbf{p}}_n^T = (\hat{p}_{nb}^T, b \in \mathcal{O}(n))$ are updated through solving the following optimization problem (41) while $\hat{\mathbf{p}}_{-n}^T(t_i) = (\hat{p}_1^T(t_i), \dots, \hat{p}_{n-1}^T(t_i), \hat{p}_{n+1}^T(t_i), \dots, \hat{p}_N^T(t_i))$ are fixed.

$$\begin{aligned} \max_{\hat{\mathbf{p}}_n^T} \quad & \sum_{n \in \mathcal{N}} \sum_{b \in \mathcal{O}(n)} \left[\omega_{nb}^{f*}(t) \Psi_{nb}(\hat{\mathbf{p}}_n^T, \hat{\mathbf{p}}_{-n}^T(t_i)) \right. \\ & \left. + (E_n(t) - \theta_n^E) e^{\hat{p}_{nm}^T(t)} \right] \quad (41) \\ \text{s.t.} \quad & \log \left(\sum_{b \in \mathcal{O}(n)} e^{\hat{p}_{nm}^T(t)} \right) - \log(P_n^{\max}) \leq 0, \forall n \in \mathcal{N} \end{aligned}$$

5) *Energy management*: For each node $n \in \mathcal{N}$, we have the optimization problem of $(e_n(t), g_n(t))$ as follows,

$$\begin{aligned} \min : \quad & (E_n(t) - \theta_n^E) \mathbf{1}_{n \in \mathcal{N}_H \cup \mathcal{N}_M} \cdot e_n(t) + [(E_n(t) - \theta_n^E) \\ & + V(1 - \varpi_1) \varpi_2 S_n^G(t)] \mathbf{1}_{n \in \mathcal{N}_Y \cup \mathcal{N}_M} \cdot g_n(t) \quad (42) \\ \text{s.t.} : \quad & 0 \leq e_n(t) \leq h_n(t) \\ & 0 \leq g_n(t) \leq g_n^{\max} \\ & \mathbf{1}_{n \in \mathcal{N}_H \cup \mathcal{N}_M} \cdot e_n(t) + \mathbf{1}_{n \in \mathcal{N}_Y \cup \mathcal{N}_M} \cdot g_n(t) + E_n(t) \\ & \leq \theta_n^E \end{aligned}$$

We can see energy management is composed of energy harvesting, energy purchasing and battery charge. Since $P_n^G(t)$ is increasing and continuous convex on $g_n(t)$ for each $S_n^G(t)$, the problem (42) turns out to be a standard convex optimization problem in $(e_n(t), g_n(t))$ and can be solved efficiently.

V. ALGORITHM PERFORMANCE

At the beginning of the algorithm performance analysis, we will give an assumption that there exists $\delta > 0$ such that

$$\tilde{C}_{nm}(\mathbf{p}^T(t), \mathbf{S}^C(t)) \leq \delta p_{nm}^T(t), \forall n \in \mathcal{N}, \forall m \in \mathcal{O}(n) \quad (43)$$

Then we can have the theorems as follows.

Theorem 2. Assume $\max\{\varepsilon_n^f, \mu_{\max}^{in} + R_{\max}\} \leq D_{\max}$ holds, where μ_{\max}^{in} denotes the maximal amount of packets that node n can receive from other nodes in one slot. Then under the

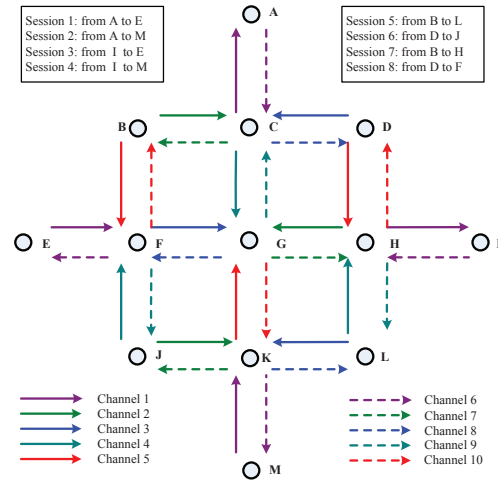


Fig. 1. Network topology.

algorithm CLCA with any fixed parameter $V > 0$, all queues are bounded for $t > 0$, as follows

$$E_n(t) \leq \theta_n^E, Z_n^f(t) \leq Z_{\max}, \tilde{Q}_n^f(t) \leq \tilde{Q}_{\max}, Q_n^f(t) \leq Q_{\max}$$

Provided that

$$E_n(0) \leq \theta_n^E, Z_n^f(0) \leq Z_{\max}, \tilde{Q}_n^f(0) \leq \tilde{Q}_{\max}, Q_n^f(0) \leq Q_{\max}$$

Where the queue bounds are given by

$$\theta_n^E = 2\delta V \varpi_1 \beta_n^f + P_{n,\max}^{Total} + \delta(\mu_{\max}^{in} + R_{\max} + \varepsilon_n^f) \quad (44)$$

$$Z_{\max} = V \varpi_1 \beta_n^f + R_{\max} \quad (45)$$

$$\tilde{Q}_{\max} = V \varpi_1 \beta_n^f + \varepsilon_n^f \quad (46)$$

$$Q_{\max} = V \varpi_1 \beta_n^f + \mu_{\max}^{in} + R_{\max} \quad (47)$$

Proof: Please see Appendix B.

Theorem 3. Suppose random state vector $\varphi(t) = [\mathbf{S}^C(t), \mathbf{S}^H(t), \mathbf{S}^G(t)]$ is i.i.d. over slots and any C-additive approximation¹ for minimizing RHS of (31) is used such that (33)-(42) hold. And $E_n(0) \leq \theta_n^E$ for $\forall n \in \mathcal{N}$, $Z_n^f(0) \leq Z_{\max}$, $\tilde{Q}_n^f(0) \leq \tilde{Q}_{\max}$, $Q_n^f(0) \leq Q_{\max}$ for $\forall f \in \mathcal{F}$ and $\forall n \in \mathcal{N}$ are satisfied. Then the achieved utility satisfies:

$$\lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}\{\phi(\tau)\} \geq \phi^* - (B + C)/V \quad (48)$$

Where B is defined in (32), ϕ^* is the optimal value associated with the problem **P1**.

Proof: Please see Appendix C.

Theorem 4. When node n allocates nonzero power for data sensing, compression or/and transmission, we have:

$$E_n(t) \geq p_{n,\max}^{Total}, n \in \mathcal{N} \quad (49)$$

Proof: Please see Appendix D.

VI. PERFORMANCE EVALUATION

In this section, we will present the simulation results for our proposed algorithm CLCA.

¹Please see the definition of C-additive approximation in Definition 4.7 of [32].

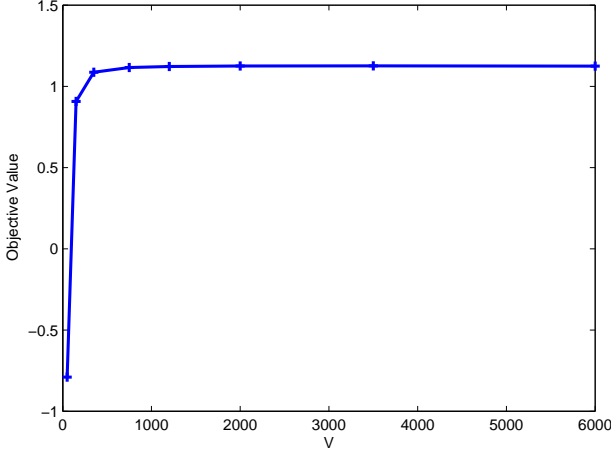


Fig. 2. Objective value achieved by CLCA.

A. Simulation setting

At first, we give the network topology as presented in Fig.1. In the topology, we consider a multi-channel WSNs with 13 nodes, 32 links, 8 flows/sessions transmitted on 10 different channels. We set $\mathcal{N}_H = \{A, C, E, H, J\}$, $\mathcal{N}_G = \{B, F, G, L, M\}$, $\mathcal{N}_M = \{D, I, K\}$ as the default scenario.

The channel state matrix $S^C(t)$ has independent entries for every link are uniformly distributed with interval $[S_{\min}^C, S_{\max}^C] \times d^{-4}$, where $S_{\min}^C = 0.9$, $S_{\max}^C = 1.1$, d denotes the distance between transmitter and receiver of the link. The energy-harvesting vector $S^H(t)$ and the electricity price vector $S^G(t)$ both have independent entries that are uniformly distributed in $[0, h_{\max}]$ and $[S_{\min}^G, S_{\max}^G]$ respectively, where $h_{\max} = 2$, $S_{\min}^G = 0.5$ and $S_{\max}^G = 1$. All statistics of $S^C(t)$, $S^H(t)$ and $S^G(t)$ are i.i.d. across time-slots.

Furthermore, we set the electricity cost function as $P_n^G(t) = S_n^G(t)$ and all the initial queue size to be zero and several default values as follows: $\varpi_1 = 0.5$, $\varpi_2 = 1$, $\delta = 2$, $\rho = 3$, $N_0^b = 5 \times 10^{-13}$, $R_{\max} = 3$, $\mu_{\max} = 1.5$, $D_{\max} = 9$, $\varepsilon_n^f = 6$, $\beta_n^f = 1$, $\forall n \in \mathcal{N}, \forall f \in \mathcal{F}$, $\hat{p}_f^S = 0.1, \forall f \in \mathcal{F}$, $P_{\max}^n = 2$, $\hat{p}_n^R = 0.05, \forall n \in \mathcal{N}$, $g_n^{\max} = 2, \forall n \in \mathcal{N}_G \cup \mathcal{N}_M$. According to (4), we set the optimal value of ρ^* as XXXX to achieve the minimal worst case delay. we set $V = [50 \ 150 \ 350 \ 750 \ 1200 \ 2000 \ 3500 \ 6000]$. In all simulations, the simulation time is set to be 3×10^5 time slots.

B. Verification of theoretic claims

Fig.2 presents the result of the objective value achieved by CLCA with different values of V . Our objective is composed of by two parts, i.e., the throughput utility and the electricity cost. Fig.2 shows that the objective value is increased with an increasing V and is arbitrary close to optimal value when V is large enough. This confirms the results of Theorem 3.

Fig. 3 presents the total time-average backlog in the network for six kinds of queues. From Fig. 3, we observe that all queue backlogs linearly increases with increasing V . This shows a good match between the simulations and the claims of Theorem 1 and Theorem 2.

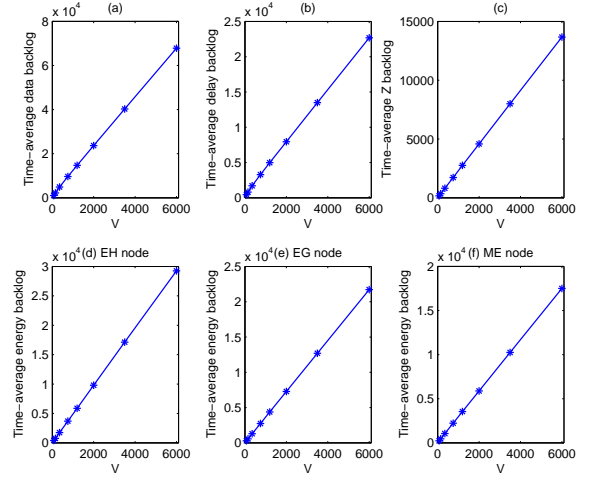


Fig. 3. Time average of total queue backlog in the network versus V .

C. Performance comparison

Also, we provide comparisons with the existing method proposed in [30] with the different virtual delay queue structure for achieving the worst case delay guarantees in single-hop and multi-hop networks. Here, the virtual delay queue structure, i.e., Eq. (3) in [30] is applied in the the scenario discussed in this paper. Throughout the section and in plots, we refer to the method using the virtual queue structure proposed in [30] by *NeelyOpportunistic*.

In Fig. (4), we plot the result of the objective value achieved by *NeelyOpportunistic* with different values of V . It is seen that the performance of *NeelyOpportunistic* is much inferior to that of our proposed Algorithm CLCA. The reasons is that the virtual queue structure proposed in [30] brings about the serious packet drop, and leads to the ultra-low throughput. In contrast, the virtual queue structure, Eq. (2a)(2b) used in our proposed Algorithm CLCA can achieve the zero packet drop in most case, shown in Fig. (5).

We further give the detailed situation of the packet drop of session 1 in node A at $V = 750$ in Fig.6. As the green line presented in Fig.6, there is no packet drop in our proposed algorithm CLCA. In contrast, as the red line presented in Fig.6, there is ultra-highly frequent packet drop in *NeelyOpportunistic*.

VII. CONCLUSIONS

In this paper, we will address cross-layer control to guarantee worse case delay for Heterogeneous Powered (HP) WSNs. We design a novel virtual delay queue structure, and apply the Lyapunov optimization technique to develop a cross-layer control algorithm CLCA for HPWSNs that: (1) provide efficient throughput-utility, (2) guarantee bounded worst-case delay, and (3) are robust to general time-varying conditions. We develop a novel virtual delay queue scheme to share the burden of actual packet queue backlogs to guarantee specific delay performances and finite data buffer sizes. We analyze the performance of the proposed algorithm and verify the theoretic claims through the simulation results. Compared to the existing

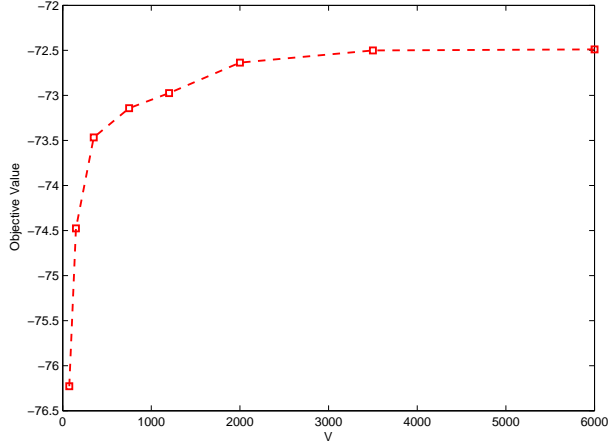


Fig. 4. Objective value achieved by *NeelyOpportunistic*.

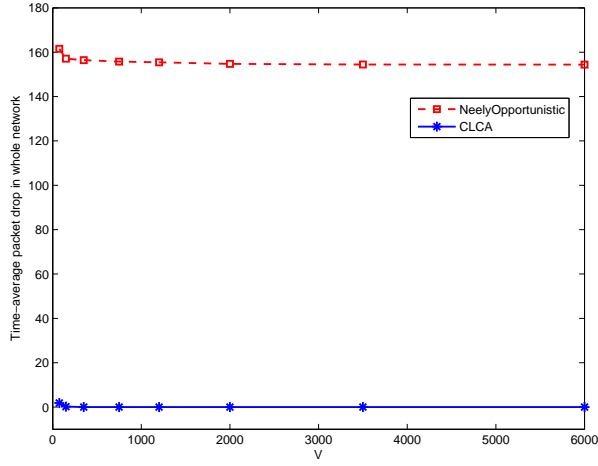


Fig. 5. Time-average number of dropped packets versus V .

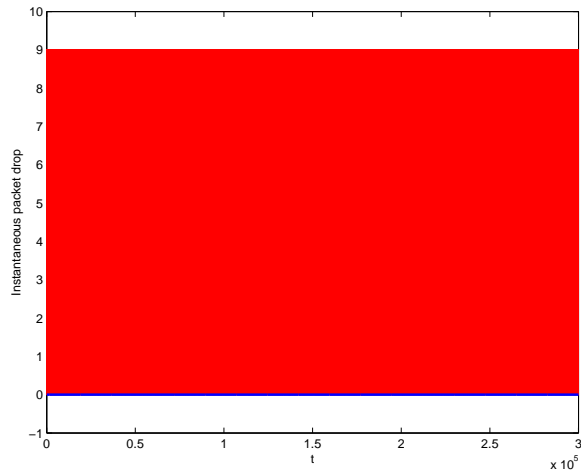


Fig. 6. Detailed situation of dropped packets at $V=750$.

works, the algorithm presented in this paper achieve much higher optimal objective without data drop through developing novel virtual queue structure.

APPENDIX A PROOF OF THEOREM 1

Assume that for any slot $\tau \in \{t, \dots, t + W_n^f + 1\}$, the condition $Q_n^f(t) > \rho \tilde{Q}_n^f(t)$ will always be satisfied, take the beginning slot $\tau = t + 1$, then by (2a), we have

$$\begin{aligned} \tilde{Q}_n^f(t + W_n^f + 1) &= \tilde{Q}_n^f(t + 1) \\ &- \sum_{\tau=t+1}^{\tau=t+W_n^f} \left(\sum_{b \in \mathcal{O}(n)} \mu_{nb}^f(\tau) + D_n^f(\tau) \right) + W_n^f \varepsilon_n^f \end{aligned}$$

Owing to $\tilde{Q}_n^f(t) \leq \tilde{Q}_{\max}$, then we have

$$\begin{aligned} W_n^f \varepsilon_n^f &\leq \sum_{\tau=t+1}^{\tau=t+W_n^f} \left(\sum_{b \in \mathcal{O}(n)} \mu_{nb}^f(\tau) + D_n^f(\tau) \right) + \tilde{Q}_{\max} \\ &+ \tilde{Q}_n^f(t + W_n^f + 1) \end{aligned} \quad (50)$$

Suppose that the following inequality is satisfied,

$$\sum_{\tau=t+1}^{\tau=t+W_n^f} \left(\sum_{b \in \mathcal{O}(n)} \mu_{nb}^f(\tau) + D_n^f(\tau) \right) \geq Q_n^f(t + 1)$$

it means that the end of the backlog $Q_n^f(t + 1)$ have been cleared during the interval $\tau \in \{t + 1, \dots, t + W_n^f\}$, and this goes against with our suppose that the worst case delay is W_n^f . So we can get

$$\sum_{\tau=t+1}^{\tau=t+W_n^f} \left(\sum_{b \in \mathcal{O}(n)} \mu_{nb}^f(\tau) + D_n^f(\tau) \right) < Q_n^f(t + 1) \quad (51)$$

Combining (50) and (51),

$$\begin{aligned} W_n^f \varepsilon_n^f &\leq Q_n^f(t + 1) + \tilde{Q}_n^f(t + W_n^f + 1) + \tilde{Q}_{\max} \\ &\leq Q_n^f(t + 1) + Q_n^f(t + W_n^f + 1) / \rho + \tilde{Q}_{\max} \\ &\leq \left[(1 + \rho) Q_{\max} + \rho \tilde{Q}_{\max} \right] / \rho \end{aligned}$$

Then we can get

$$W_n^f \leq \left[(1 + \rho) Q_{\max} + \rho \tilde{Q}_{\max} \right] / (\rho \varepsilon_n^f) \quad (52)$$

Similarly, assume that for any slot $\tau \in \{t, \dots, t + W_n^f + 1\}$, the condition $Q_n^f(t) \leq \rho \tilde{Q}_n^f(t)$ will always be satisfied, we have

$$\begin{aligned} \tilde{Q}_n^f(t + W_n^f + 1) &= \tilde{Q}_n^f(t + 1) \\ &+ W_n^f (\varepsilon_n^f - \mu_{\max}^{\text{out}} - D_{\max}) \end{aligned}$$

Thus:

$$\begin{aligned} W_n^f (\mu_{\max}^{\text{out}} + D_{\max} - \varepsilon_n^f) &= \tilde{Q}_n^f(t + 1) - \tilde{Q}_n^f(t + W_n^f + 1) \\ &\leq 2\tilde{Q}_{\max} \end{aligned}$$

So we can get:

$$W_{\max}^f \leq 2\tilde{Q}_{\max} / (\mu_{\max}^{\text{out}} + D_{\max} - \varepsilon_n^f) \quad (53)$$

Combining (52) and (53), the theorem is proved.

APPENDIX B
PROOF OF THEOREM 2

We prove Theorem 2 by induction.

Induction Basis: At time slot 0, the beginning of data sessions, all queues are empty. Then, we have following conditions for $\forall n \in \mathcal{N}, \forall f \in \mathcal{F}$.

$$\begin{aligned} Z_n^f(0) &= 0 \leq V\varpi_1\beta_n^f + R_{\max} = Z_{\max} \\ \tilde{Q}_n^f(0) &= 0 \leq V\varpi_1\beta_n^f + \varepsilon_n^f = \tilde{Q}_{\max} \\ Q_n^f(0) &= 0 \leq V\varpi_1\beta_n^f + \mu_{\max}^{in} + R_{\max} = Q_{\max} \end{aligned}$$

Induction Step: Suppose that $\forall n \in \mathcal{N}, \forall f \in \mathcal{F}$, $Z_n^f(t) \leq Z_{\max}$, $\tilde{Q}_n^f(t) \leq \tilde{Q}_{\max}$, $Q_n^f(t) \leq Q_{\max}$. Then for any $Z_n^f(t)$, $\tilde{Q}_n^f(t)$ and $Q_n^f(t)$, we have the following possible cases.

- $0 \leq Z_n^f(t) \leq V\varpi_1\beta_n^f$ or $V\varpi_1\beta_n^f < Z_n^f(t) \leq Z_{\max}$;
- $0 \leq \tilde{Q}_n^f(t) \leq V\varpi_1\beta_n^f$ or $V\varpi_1\beta_n^f < \tilde{Q}_n^f(t) \leq \tilde{Q}_{\max}$;
- $0 \leq Q_n^f(t) \leq V\varpi_1\beta_n^f$ or $V\varpi_1\beta_n^f < Q_n^f(t) \leq Q_{\max}$;

- We first analyze the size of $Z_n^f(t)$:

- If $0 \leq Z_n^f(t) \leq V\varpi_1\beta_n^f$, according to (16) we have

$$\begin{aligned} Z_n^f(t+1) &\leq Z_n^f(t) + R_{\max} \\ &\leq V\varpi_1\beta_n^f + R_{\max} \end{aligned}$$

where the first inequality is due to the fact that Z_n^f can increase by at most R_{\max} in one slot, and the second inequality is according to our proposed assumption.

- If $V\varpi_1\beta_n^f < Z_n^f(t) \leq Z_{\max}$, then

$$\begin{aligned} &V\varpi_1 \cdot U_n^f(\tilde{r}_n^f(t)) - Z_n^f(t)\tilde{r}_n^f(t) \\ &\leq V\varpi_1 \cdot U_n^f(0) + V\varpi_1\beta_n^f\tilde{r}_n^f(t) - Z_n^f(t)\tilde{r}_n^f(t) \\ &= V\varpi_1 \cdot U_n^f(0) + (V\varpi_1\beta_n^f - Z_n^f(t))\tilde{r}_n^f(t) \\ &\leq V\varpi_1 \cdot U_n^f(0) \\ &= 0 \end{aligned}$$

where the first inequality is due to the fact that β_n^f is the maximum derivative of the $U_n^f(\tilde{r}_n^f(t))$ function. Then we can get that $V\varpi_1 \cdot U_n^f(\tilde{r}_n^f(t)) - Z_n^f(t)\tilde{r}_n^f(t)$ is a non-positive value. According to the sub-problem (34), if $Z_n^f(t) > V\varpi_1\beta_n^f$, we will choose $\tilde{r}_n^f(t) = 0$. Then according to (16), we have $Z_n^f(t+1) \leq Z_n^f(t)$.

So far, we prove that $Z_n^f(t) \leq Z_{\max}$, $\forall n \in \mathcal{N}, \forall f \in \mathcal{F}$ for each time slot t .

- Next, we analyze the size of $\tilde{Q}_n^f(t)$:

- If $0 \leq \tilde{Q}_n^f(t) \leq V\varpi_1\beta_n^f$, then

$$\tilde{Q}_n^f(t+1) \leq \tilde{Q}_n^f(t) + \varepsilon_n^f \leq V\varpi_1\beta_n^f + \varepsilon_n^f$$

The first inequality is due to the fact that the queue $\tilde{Q}_n^f(t)$ can increase by at most ε_n^f in one slot.

- If $V\varpi_1\beta_n^f \leq \tilde{Q}_n^f(t) \leq \tilde{Q}_{\max}$, we can see that $D_n^f(t) = D_{\max}$ according to sub-problem (35). Since the condition $\varepsilon_n^f \leq D_{\max}$ is satisfied, we have

$$\tilde{Q}_n^f(t+1) \leq \tilde{Q}_n^f(t) - D_{\max} + \varepsilon_n^f \leq \tilde{Q}_n^f(t)$$

Up to now, we prove that $\tilde{Q}_n^f(t) \leq \tilde{Q}_{\max}$, $\forall n \in \mathcal{N}, \forall f \in \mathcal{F}$ for each time slot t .

- Now, we analyze the size of $Q_n^f(t)$:

- If $0 \leq Q_n^f(t) \leq V\varpi_1\beta_n^f$, then we can get the below inequality according to (1):

$$\begin{aligned} Q_n^f(t+1) &\leq Q_n^f(t) + \sum_{a \in \mathcal{I}(n)} \mu_{an}^f(t) + \mathbf{1}_n^f R_n^f(t) \\ &\leq V\varpi_1\beta_n^f + \mu_{\max}^{in} + R_{\max} \end{aligned}$$

- If $V\varpi_1\beta_n^f < Q_n^f(t) \leq Q_{\max}$, we have $D_n^f(t) = D_{\max}$ according to sub-problem (35). Since the data queue can increase by at most $\mu_{\max}^{in} + R_{\max}$ according to (1), we have

$$\begin{aligned} Q_n^f(t+1) &\leq Q_n^f(t) - D_{\max} + \mu_{\max}^{in} + R_{\max} \\ &\leq Q_n^f(t) \end{aligned}$$

Up to now, we prove that $Q_n^f(t) \leq Q_{\max}$, $\forall n \in \mathcal{N}, \forall f \in \mathcal{F}$ for each time slot t .

So we complete the proof of Theorem 2. \square

APPENDIX C
PROOF OF THEOREM 3

We denote $\alpha_{n,f}^Q$, $\alpha_{n,f}^{\tilde{Q}}$, $\alpha_{n,f}^Z$, α_n^E and $\mu_{n,f}^Q$, $\mu_{n,f}^{\tilde{Q}}$, $\mu_{n,f}^Z$, μ_n^E as the input and output of the queue $Q_n^f(t)$, $\tilde{Q}_n^f(t)$, $Z_n^f(t)$, $E_n(t)$ for $\forall f \in \mathcal{F}, n \in \mathcal{N}$, respectively. Denote $\mathbf{I}(t) = (\tilde{\mathbf{r}}(t), \mathbf{r}(t), \mathbf{D}(t), \mathbf{p}^T(t), \boldsymbol{\mu}(t), \mathbf{e}(t), \mathbf{g}(t))$ as the vector of variables of the problem **P1**. According to the Optimality over ω -only policies theorem (Theorem 4.5 in [32]). For all $\eta > 0$, there exists an φ -only policy \mathbf{I}^* that chooses $\mathbf{I}^*(t) \in \mathcal{I}_{\varphi(t)}$ as a random function of random state $\varphi(t)$, where $\mathcal{I}_{\varphi(t)}$ is an abstract set that defines decision options under state $\varphi(t)$, such that:

$$\phi(\mathbf{I}^*(t), \varphi(t)) = \phi^* \quad (54)$$

$$\mathbb{E}\left\{\alpha_{n,f}^Q(\mathbf{I}^*(t), \varphi(t))\right\} \leq \mathbb{E}\left\{\mu_{n,f}^Q(\mathbf{I}^*(t), \varphi(t))\right\} + \eta \quad (55)$$

$$\mathbb{E}\left\{\alpha_{n,f}^{\tilde{Q}}(\mathbf{I}^*(t), \varphi(t))\right\} \leq \mathbb{E}\left\{\mu_{n,f}^{\tilde{Q}}(\mathbf{I}^*(t), \varphi(t))\right\} + \eta \quad (56)$$

$$\mathbb{E}\left\{\alpha_{n,f}^Z(\mathbf{I}^*(t), \varphi(t))\right\} \leq \mathbb{E}\left\{\mu_{n,f}^Z(\mathbf{I}^*(t), \varphi(t))\right\} + \eta \quad (57)$$

$$\mathbb{E}\left\{\alpha_n^E(\mathbf{I}^*(t), \varphi(t))\right\} \leq \mathbb{E}\left\{\mu_n^E(\mathbf{I}^*(t), \varphi(t))\right\} + \eta \quad (58)$$

$$0 \leq \tilde{r}_n^{f*}(t) \leq R_{\max} \quad f \in \mathcal{F} \quad (59)$$

$$0 \leq r_n^{f*}(t) \leq R_{\max} \quad f \in \mathcal{F} \quad (60)$$

$$0 \leq D_n^{f*}(t) \leq D_{\max} \quad f \in \mathcal{F}, n \in \mathcal{N} \quad (61)$$

$$0 \leq e_n^*(t) \leq h_n(t) \quad n \in \mathcal{N} \quad (62)$$

$$0 \leq g_n^*(t) \leq g_n^{\max} \quad n \in \mathcal{N} \quad (63)$$

$$0 \leq h_n^*(t) \leq h_{\max} \quad n \in \mathcal{N} \quad (64)$$

$$\mathbf{I}^*(t) \in \mathcal{I}_{\varphi(t)} \quad (65)$$

The C-additive approximation ensures by (30):

$$\begin{aligned}
\Delta_V(\Psi(t)) &\leq B + C - V\mathbb{E}\{\phi(\mathbf{I}^*(t), \varphi(t)) | \Psi(t)\} \\
&+ \sum_{n \in \mathcal{N}} \sum_{f \in \mathcal{F}} Q_n^f(t) \mathbb{E}\left\{\alpha_{n,f}^Q(\mathbf{I}^*(t), \varphi(t)) \right. \\
&\quad \left. - \mu_{n,f}^Q(\mathbf{I}^*(t), \varphi(t)) | \Psi(t)\right\} \\
&+ \sum_{n \in \mathcal{N}} \sum_{f \in \mathcal{F}} \tilde{Q}_n^f(t) \mathbb{E}\left\{\alpha_{n,f}^{\tilde{Q}}(\mathbf{I}^*(t), \varphi(t)) \right. \\
&\quad \left. - \mu_{n,f}^{\tilde{Q}}(\mathbf{I}^*(t), \varphi(t)) | \Psi(t)\right\} \\
&+ \sum_{n \in \mathcal{N}_s} \sum_{f \in \mathcal{F}_n} Z_n^f(t) \mathbb{E}\left\{\alpha_{n,f}^Z(\mathbf{I}^*(t), \varphi(t)) \right. \\
&\quad \left. - \mu_{n,f}^Z(\mathbf{I}^*(t), \varphi(t)) | \Psi(t)\right\} \\
&+ \sum_{n \in \mathcal{N}} (E_n(t) - \theta_n^E) \mathbb{E}\left\{\alpha_n^E(\mathbf{I}^*(t), \varphi(t)) \right. \\
&\quad \left. - \mu_n^E(\mathbf{I}^*(t), \varphi(t)) | \Psi(t)\right\} \quad (66)
\end{aligned}$$

Substituting the φ -only policy from (54)-(65) in RHS of the above inequality (66) and taking $\eta \rightarrow 0$, then

$$\Delta_V(\Psi(t)) \leq B + C - V\phi^* \quad (67)$$

Combining (67) with (26)-(29) and using iterated expectations and telescoping sums for all $t > 0$:

$$\frac{1}{t} \sum_{\tau=0}^{t-1} \phi(\tau) \geq \phi^* - (B + C) / V - \mathbb{E}\{L(\Psi(0))\} / (Vt)$$

Taking $t \rightarrow \infty$, we can get that:

$$\lim_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}\{\phi(\tau)\} \geq \phi^* - (B + C) / V$$

So we complete the proof of Theorem 3. \square

APPENDIX D PROOF OF THEOREM 4

According to the definition of the link capacity, we can get that the inequality (68) holds.

$$\tilde{C}_{ab}(\mathbf{p}^T(t), \mathbf{S}^C(t)) \leq \tilde{C}_{ab}(\mathbf{p}^{T'}(t), \mathbf{S}^C(t)) \quad (68)$$

Where $\tilde{C}_{ab}(\mathbf{p}^{T'}(t), \mathbf{S}^C(t))$ obtained by setting $p_{nm}^T(t)$ of $\mathbf{p}^T(t)$ to zero, $(n, m) \in \mathcal{L}$, $(a, b) \in \mathcal{L}$ and $(n, m) \neq (a, b)$.

Then we can see the weight of session f over link (n, m) satisfied:

$$\begin{aligned}
\omega_{nm}^f(t) &= Q_n^f(t) - Q_m^f(t) + (E_m(t) - \theta_m^E) \tilde{p}_m^R + \tilde{Q}_n^f(t) \\
&\leq Q_n^f(t) + \tilde{Q}_n^f(t) \\
&\leq 2V\varpi_1\beta_n^f + \mu_{\max}^{in} + R_{\max} + \varepsilon_n^f \quad (69)
\end{aligned}$$

Suppose $E_n(t) < p_{n,\max}^{Total}$ when node $n \in \mathcal{N}$ allocates nonzero power for data sensing, compression or transmission and the power allocation control vector \mathbf{p}^{T*} is the optimal solution to sub-problem (38). Without loss of generality, there should be some $p_{mn}^{T*}(t) > 0$. We can get a vector \mathbf{p}^T by setting

$p_{mn}^{T*}(t) = 0$. Let $G(\mathbf{p}^T(t), \mathbf{S}^C(t))$ denote the objective function of sub-problem (38), so we have

$$\begin{aligned}
&G(\mathbf{p}^{T*}(t), \mathbf{S}^C(t)) - G(\mathbf{p}^T(t), \mathbf{S}^C(t)) \\
&= \sum_{n \in \mathcal{N}} \sum_{b \in \mathcal{O}(n)} \left[\tilde{C}_{nb}(\mathbf{p}^{T*}(t), \mathbf{S}^C(t)) \right. \\
&\quad \left. - \tilde{C}_{nb}(\mathbf{p}^T(t), \mathbf{S}^C(t)) \right] \omega_{nb}^{f*}(t) + (E_n(t) - \theta_n^E) p_{nm}^{T*}(t) \quad (70) \\
&\leq \tilde{C}_{nm}(\mathbf{p}^{T*}(t), \mathbf{S}^C(t)) \omega_{nb}^{f*}(t) + (E_n(t) - \theta_n^E) p_{nm}^{T*}(t) \quad (71) \\
&\leq \delta p_{nm}^{T*}(t) (2V\varpi_1\beta_n^f + \mu_{\max}^{in} + R_{\max} + \varepsilon_n^f) \\
&\quad - (p_{n,\max}^{Total} - \theta_n^E) p_{nm}^{T*}(t) \quad (72) \\
&= 0 \quad (73)
\end{aligned}$$

where (70) is obtained by the sub-problem (38). We can get (71) by $\tilde{C}_{nb}(\mathbf{p}^{T*}(t), \mathbf{S}^C(t)) \leq \tilde{C}_{nb}(\mathbf{p}^T(t), \mathbf{S}^C(t))$, $b \neq m$ according to (68). Combining the assumption $E_n(t) < p_{n,\max}^{Total}$ with (43), (69) and (71), we can get (72). And combining (72) with the energy queue upperbound (44), we can get (73). So we can see that \mathbf{p}^{T*} is not the optimal solution to (38), which is inconsistent with our assumption. Then we have $E_n(t) \geq p_{n,\max}^{Total}$. So we complete the proof of Theorem 4. \square

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